A combination of KNN-PTV and physics-constrained RBFs for super-resolution in image velocimetry

Iacopo Tirelli[1,*] , Miguel Alfonso Mendez[2] , Andrea Ianiro[1] and Stefano Discetti[1]
1: Universidad Carlos III de Madrid, Aerospace Engineering Research Group, Madrid, Spain
2: von Karman Institute for Fluid Dynamics, Environmental and Applied Fluid Dynamics, Sint-Genesius-Rode, Belgium
* Correspondent author: iacopo.tirelli@uc3m.es

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ABSTRACT This paper presents a novel super-resolution approach for image velocimetry, which combines K-Nearest-Neighbours Particle Tracking Velocimetry (Tirelli et al., 2023, KNN-PTV) with constrained Radial Basis Functions (Sperotto et al., 2022, c-RBFs) regression. KNN-PTV improves the spatial resolution of a vector field by leveraging data coherence in space and time, while c-RBF enables the computation of an analytical vector field that adheres to physical constraints such as no-slip conditions at walls or the divergence-free for incompressible flows. We investigate the potential of the KNN-RBF combination in 2D and 3D applications, which are challenging for traditional methods due to sparser particle distributions. This extension is the focus of our ongoing research and will be discussed in detail in our upcoming conference contribution.

1 INTRODUCTION

The methodology presented in this paper aims to improve the spatial resolution of Particle Image Velocimetry (PIV) or Particle Tracking Velocimetry (PTV) by combining the ensemble approach of KNN-PTV (Tirelli et al., 2023) with constrained regression using Radial Basis Functions (cRBFs), as proposed in Sperotto et al. (2022). KNN-PTV identifies similar flow structures at different time instants using a large ensemble of statistically independent snapshots, allowing for the enhancement of spatial resolution by merging particle vectors from different snapshots. The algorithm splits the measurement domain into subdomains to enforce similarity on a local scale and then uses an unsupervised KNN search in the space of significant flow features obtained through Proper Orthogonal Decomposition (POD) of the original data obtained via cross-correlation in PIV or binning in PTV. The enhanced fields obtained by KNN-PTV are then fed into the cRBFs regression to achieve super-resolution. This algorithm approximates the velocity field as a linear combination of RBFs, which is constrained to respect physical priors such as boundary conditions or solenoidal conditions. The analytical approximating functions can be evaluated (and differentiated) on any grid.
The goal of this combination is to leverage the complementary strengths of KNN-PTV and c-RBFs to achieve physically constrained super-resolution by exploiting the space-time coherency of the data. In the preliminary combination presented in this work, the cRBF is fed with fields whose local density is increased via KNN-PTV.

2 VALIDATION AND PRELIMINARY RESULTS

The algorithm proposed was tested using synthetic PTV data derived from a direct numerical simulation (DNS) of a turbulent channel flow obtained from the Johns Hopkins Turbulence Database (http://turbulence.pha.jhu.edu/). The dimensions of the channel consist of 2 half-channel-heights h from wall to wall, $3\pi h$ in the span-wise direction and $8\pi h$ in the streamwise direction. For all simulation settings, please refer to Li et al. (2008). In this simulated experiment, subdomains of $2h \times h$ are extracted in the streamwise and wall-normal directions, respectively. The resolution is set at 512 pixels/h and the particle image density is 0.01 particles per pixel. To reduce the correlation between different samples, the snapshots are generated with a time separation of 1 convective time. A large number of snapshots are extracted by exploiting flow homogeneity in the streamwise and spanwise directions. The subdomains are separated by $2h$ in the streamwise and $0.25h$ in the spanwise direction, resulting in a total of 11856 generated snapshots. The exact particles position fed the KNN-PTV to avoid errors from blending snapshots of other sources due to the image pairing process. The performance of the algorithm was evaluated using the normalized root mean square error δ_{RMS} as a metric, defined in Equation 7 of Tirelli et al. (2023).
The contours of the instantaneous stream-wise velocity field estimated by standard PIV with an interrogation window of 32x32 pixels, KNN-PTV and KNN-PTV combined with RBF, along with the reference field from the original DNS, are shown in

Figure 1. Table 1 shows the spatial average of the root mean square error δ_{RMS} evaluated for all the above-mentioned application.

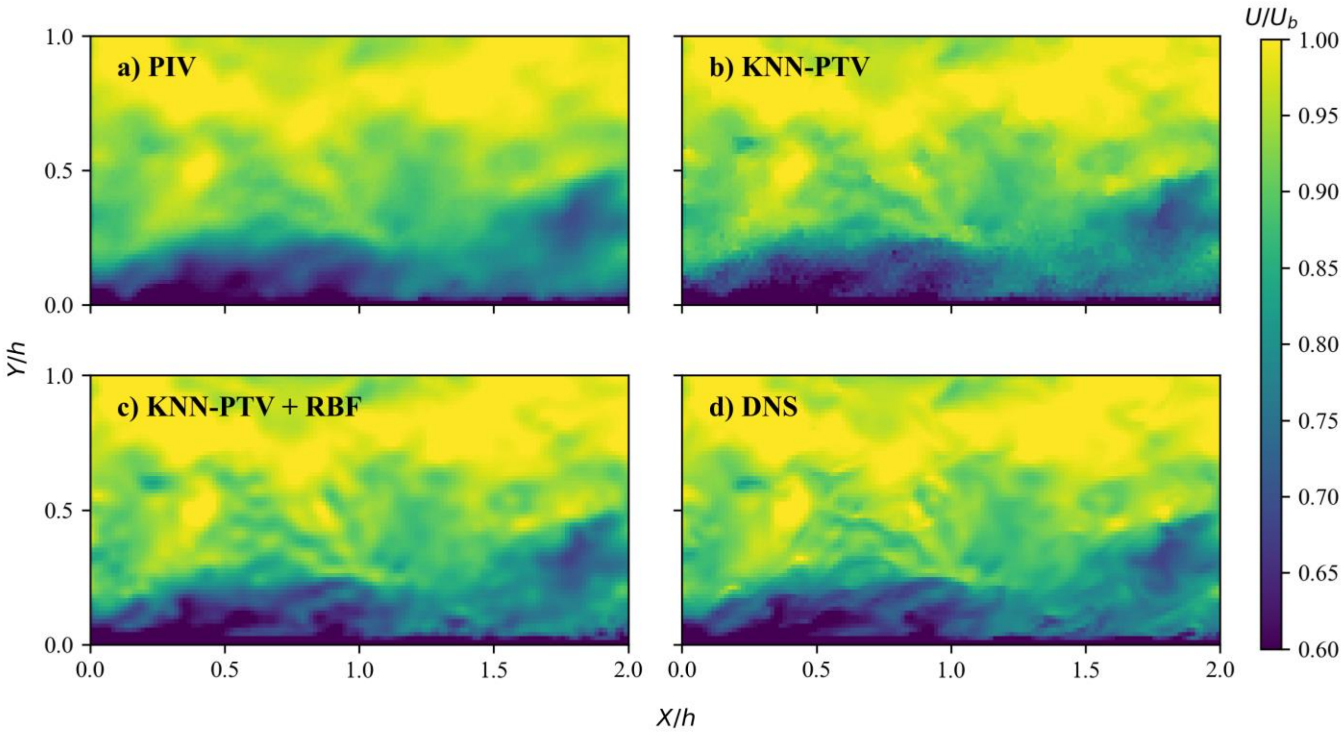

Figure 1. Instantaneous stream-wise velocity field contours estimated with: (a) standard PIV with interrogation window of 32×32 pixels, (b) KNN-PTV, (c) KNNPTV + RBF. The reference field from the original DNS is included for comparison (d) .

PIV IW = 32	KNN-PTV	KNN-PTV + RBF
0.0222	0.0196	0.0173

Table 1. Spatial average of the root mean square error $\langle\delta_{RMS}\rangle$ evaluated for PIV with interrogation window of 32 pixels, KNN-PTV and KNN-PTV with the help of RBF.

The preliminary results of the new methodology demonstrate promising accuracy in reconstruction. The benchmarking was performed against standard PIV with an interrogation window of 32 pixels, simulated by filtering the data with a moving average and down-sampling the result, and the stand-alone implementation of the KNN-PTV. From both the methodology the bias error due to modulation effect has been removed as explained in Tirelli et al.(2023). The c-RBF regression was constrained to have no-slip conditions at walls. Additionally, it was applied also as a penalty. The domain contained 3104 collocation points following the clustering approach explained in Sperotto et al. (2022).
The validation of the method on experimental test cases is currently ongoing. Furthermore, the authors are working on the extension to 3D. The combination of KNN-PTV and RBF methodologies is expected to be particularly well-suited for 3D flow analysis, as the enforcement of physical constraints should be able to compensate for the larger interparticle spacing. The results of this extension and its application to more complex flows will be presented in the final conference contribution.

3 REFERENCES

- Li, Y., Perlman, E., Wan, M., Yang, Y., Meneveau, C., Burns, R., ... & Eyink, G. (2008). A public turbulence database cluster and applications to study Lagrangian evolution of velocity increments in turbulence. Journal of Turbulence, (9), N31.
- Sperotto, P., Pieraccini, S., & Mendez, M. A. (2022). A meshless method to compute pressure fields from image velocimetry. Measurement Science and Technology, 33(9), 094005.
- Tirelli, I., Ianiro, A., & Discetti, S. (2023). An end-to-end KNN-based PTV approach for high-resolution measurements and uncertainty quantification. Experimental Thermal and Fluid Science, 140, 110756.
- Tirelli, I., Ianiro, A., & Discetti, S. (2023). A simple trick to improve the accuracy of PIV/PTV data. Experimental Thermal and Fluid Science, 110872.

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